A Neural Network Approach to Physiological Joint Loading Profile Generation in the Kansas Knee Simulator

By

William M. Eboch

Submitted to the graduate degree program in Mechanical Engineering and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Master of Science.

____

Dr. Lorin Maletsky, Chairperson

____

Dr. Sara Wilson, Committee Member

____

Dr. Carl Luchies, Committee Member

Date Defended December 17, 2015

The Thesis Committee for William M. Eboch

certifies that this is the approved version of the following thesis:

A Neural Network Approach to Physiological Joint Loading Profile Creation in the Kansas Knee Simulator

Dr. Lorin Maletsky, Chairperson

Dr. Sara Wilson, Committee Member

Dr. Carl Luchies, Committee Member

Date Defended: December 17, 2014

Abstract

Replicating complex physiological joint loads in an in-vitro simulator allows for research that can be used to improve the outcome of prosthetic design, characterize knee laxity, and evaluate the mechanics of injury. Producing physiological in-vivo loads in an in-vitro simulator can prove challenging due to the complex nature of in-vitro simulators. The goal of this research was to develop a method that can accurately determine the actuator loading profiles necessary to replicate in-vivo joint loads in the Kansas Knee Simulator. Previously, an Adams model was used for profile generation, but was dependent on the fine tuning of small parameters of the system. A neural network was chosen as the basis for a new method to circumvent this issue as neural networks do not rely on information about the system to produce results. Through an iterative process the neural network's method, inputs, outputs, and necessary training data were determined. A custom built instrumented tibia was implanted into a cadaveric knee and training data was collected and used to train the neural network for a physiological walk cycle. After training, a profile was produced with an RMS error of 31.7 lbs. in the superior-inferior (S-I) direction and 3.8 lbs. in the anterior-posterior (A-P) direction. A second cadaveric knee was used to verify the profile, resulting in an RMS error of 32.4 lbs. in S-I and 12.0 lbs. in A-P. These results are promising, as variation of walk cycles measured in-vivo produced an average RMS difference of 38.3 lbs. in S-I and 7.1 lbs. in A-P. This method shows promise for use as profile generation technique, but additional research is needed to collect the training data to create more profiles in the future.

Table of Contents

Chapter 1: Introduction

Total knee arthroplasty is one of the most common surgery procedures performed in the United States with 719,000 surgeries reported in 2010 [1]. This number is only expected to climb as 3.48 million replacements are projected to occur in the year 2030 [2]. While typically considered a successful surgery, many patients still report an inability to perform certain demanding activities post operation [3]. These activities, such as squatting, kneeling and carrying loads, are important in the daily lives of total knee replacement patients. Improvements to prosthetic designs could allow for more natural knee function and developing methods to test new prosthetic designs is an important step in this process.

The use of in-vitro simulators has been vital in studying the knee joint. The use of these devices allows for testing that would be impractical or unethical to perform in-vivo. There have been countless practical uses of in-vitro simulators such as in the evaluation of total knee prosthetics prior to in-vivo implantation [4], the characterization knee motion and laxity [5], and mechanics of injury [6]. While these studies have different specific goals and use different in-vitro simulator configurations to determine results, there are a number of similarities that can be drawn between them. Most notably, these studies determine a target loading configuration and apply it to each specimen in the study. By applying a consistent loading profile to different specimen evaluations can be made that are not possible to evaluate in-vivo. In-vitro simulators reduce variability in loading conditions and allow for the examination of potential causes of variation such as surgical alignment or specimen specific variation.

The choice of loading conditions is vital as loads at the joint have been shown to be directly related to the kinematic outcome [7, 8]. Studies have used many different targets ranging from simple static loads [5], to attempts to replicate physiological activities of daily living (ADLs) [4].

As research into measuring in-vivo joint loads has progressed so too have the targets of in-vitro simulations. Previously, force plate data has been used requiring joint loads to be estimated using musculoskeletal models. [9-11]. These targets were less likely to be used by in-vitro simulators as they were estimates of joint loads rather than direct measurements. More recently, the advent of the instrumented tibia has allowed for a more direct and accurate measurement of joint loading conditions [12, 13]. These direct joint loading measurements are increasing in complexity ranging from simple deep knee bends to jogging and stair climbing. It can be assumed that as time progresses an even greater number of ADLs from more real patients will be available representing most of the activities that patients have experienced difficulty in replicating.

As direct joint measurement provides more complicated target loading conditions at the joint, a need arises to be able to efficiently replicate these joint loads using in-vitro simulators. In order to produce reliable physiological joint loading conditions with a knee simulator, an actuator loading profile needs to be determined. For this thesis, the Kansas Knee Simulator (KKS) was used for the development of loading profiles. Previously, a computation model of the KKS was built in Adams (MSC.ADAMS 2011) and was used for loading profile prediction [14]. While this method could prediction some target loading conditions, it was subject to a number of drawbacks. This method was dependent on fine tuning of small parameters such as coefficients of friction and surface contact of the joint. Small changes to the implant or the KKS created large changes in predicted outcomes and retuning the model to match the KKS proved to be time consuming and ineffective at generating profiles.

The goal of this research was to develop and validate a method that allows for the creation of physiological joint loading profiles for the KKS. Specifically, a method was developed to create a neural network, unique to a set of parameters in the KKS, which allows for the prediction of actuator loading profiles to match a target physiological joint loading profile. This neural network method allows for the accurate creation of a profile given a single configuration of the simulator. The direct feedback from an instrumented tibia allows training data to be accumulated to relate actuator loads to loads at the knee, providing an opportunity that was previously unavailable when creating the Adams model. This opens the doors for numerous research questions to be answered and paves the way for research to improvement prosthetic design.

The following thesis details the research to produce this method. Chapter two offers a literature review of relevant in-vitro simulators, target joint loads, and previous methods to generate loading profiles in the KKS. Chapter three presents a study done using the method to create a physiological walk cycle. Chapter four presents the conclusions drawn from this research and suggests future work to improve the method and increase its relevancy towards future research. The appendices contain additional information about an alternative method that was developed for the same purpose as well as other work performed to enable this research.

Chapter 2: Literature Review

In-vitro simulations have been evolving over the course of the last few decades. With the development of direct in-vivo measurement at the joint simulators have gravitated away from Oxford-style rigs, which were inspired by the use of force plate data to more direct control from robotic simulators. As these changes have developed, a number of robotic simulators have emerged utilizing these direct in-vivo loads to develop loading profiles that accurately replicate physiological joint loads. Oxford-style knee rigs typically do not have the same direct control over the loading condition at the joint due to the coupled nature of the design. In order for Oxford-style knee rigs to replicate these joint loads, a method must be developed that can accurately predict the joint loads based on actuator loading profiles. Many studies have utilized the loading data generated from these instrumented tibiae, but few have detailed the method they used to replicate the joint loads. This research aims to detail one such method, a neural network, which can predict the joint loading condition based on an adequate training data set.

In-Vivo Load Measurement

Early attempts at determining in-vivo joint loads was through the use of force plate measurements and musculoskeletal models [9]. As direct measurement of the in-vivo joint was not feasible, calculations based on force plate data were regularly used. For example, Taylor et al. detail joint load findings for both gait and stair ascent [10]. Unfortunately, there were large variations in the calculated joint loads that came from the musculoskeletal models as peak body weight calculations for a simple gait cycle varied from 3-6 times body weight [10, 11, 15]. This reduced the motivation for in-vitro simulators to match joint loads.

Many attempts have been made to get a more accurate depiction of the in-vivo joint loading condition at the knee. One of the most successful designs is an implantable tibia prosthesis with instrumented force sensors as explained by D'Lima et al. [13]. This implantable prosthesis was one of the first to directly measure in-vivo knee joint loads. The design allowed for wireless transmission of joint loads while the subject was able to perform various activities of daily living (ADLs).

The loading conditions used as a baseline throughout this research are from the in-vivo joint loads detailed by Bergmann et al. [12]. The authors developed a method to systematically record and standardize loads from seven different activities of daily living (ADLs). A novel instrumented knee implant measured forces and moments in all six-degrees-of-freedom allowing for a complete picture of the loads at the joint throughout each activity. Eight individual subjects were recorded for each of the ADLs and normalized by body weight and cycle time. Average cycles were then reported along with the individual profiles. These results have been used as a gold standard for testing knee loads due to the accuracy and repeatability of the loads.

Simulator Design

In-vitro devices range from static rigs to Oxford-style simulators to robotic arms and have been used for a multitude of analyses Each style of device suits a different purpose and a wide variety of devices exist within each of the machine types. Static loading rigs allow for constant loads to be applied to bone ends and/or musculature. Oxford-style rigs are more complex than static rigs and allow for dynamic forces to be applied to these bone ends and muscle bodies. Finally, robotic arms tend to be the most constrained and tend to move through physiological kinematic positions to simulate in-vivo conditions. While each of these in-vitro simulators play a role in the study of the knee joint, the focus of this thesis is on the KKS, an Oxford-style rig.

Oxford-style knee simulators have been used extensively for knee research. A wide variety of configurations exist, but typically these rigs apply loads at the femur, tibia, and musculature while allowing kinematic freedom of the knee joint [16-18]. The goal of these simulators is to create repeatable loading conditions while not sacrificing kinematic freedom at the joint to allow for direct kinematic comparisons. The control of these simulators typically allows for a profile that includes flexion angle as well as loads to be determined in the rest of the directions. The KKS is a five-axis hydraulic oxford-style knee simulator that applies load to the femur, tibia, and quadriceps tendon. The knee is situated upright with the femur mounted to allow for vertical translation and flexion-extension (F-E) about the hip. The tibia allows for F-E about the ankle, varus-valgus (V-V) about the ankle, and medial-lateral (M-L) translation at the ankle. There are five actuators that exert load on the knee. Three act on the sagittal plane: pulling on the quadriceps tendon, vertically on the hip, and an F-E moment about the ankle. Two actuators provide out of sagittal plane loads in M-L direction on the ankle and about the long axis of the tibia. This simulator design allows for complex loading conditions to be applied while allowing kinematic freedom at the joint. This complexity increases as joint loads are targeted as three actuators act in the sagittal plane and their contributions to the joint loads change as the knee flexes down. This illustrates one drawback of this design which are the challenges imposed when attempting to match specific joint loads.

A number of robotic knee rigs have also been developed to evaluate the knee joint. Like the Oxford-style rigs there are a great number of loading configurations and additional capabilities of these devices. Typically, these rigs fix the femur and allow a six-DOF robotic arm to manipulate the tibia about the femur [19-21]. These robotic arms usually have a load cell placed in line with the tibia that allows for load measurement to be taken in real time throughout testing. These simulators can be controlled in position control, load control, or a hybrid control that allows for switching between the two options. One common method to develop a profile with a robotic arm simulator is to step through the desired motion for the full cycle arriving at the correct static loads at a chosen interval. This allows for consistent loads or position between specimens, but is incredibly time consuming and not easily repeatable for cadaveric studies.

Use of Models of In-Vitro Simulators

In addition to in-vitro simulators, models of in-vitro simulators have been used for a variety of reasons. Models allow for a unique perspective to be reached as simulations can be done without the use of cadavers. After designing and verifying a model with in-vitro data, models of in-vitro simulators can be used to quickly evaluate changes within the knee [22, 23]. These models allow for testing that would otherwise be impractical with in-vitro simulation alone such as small surgical alignment changes [23]. After the models have been developed and verified, the model can be used as a prediction tool for the simulator. Guess and Maletsky used an Adams model of the simulator to generate actuator loading inputs that reproduce a particular patellar tendon load for a squat [14]. The method was not without fault and had many sensitivities that limited its effectiveness. The model performed well within a hip flexion range of 10-20 degrees, but outside of that range the performance suffered, likely due to insufficient modeling of the cam geometries of the components used. The exact knee parameters are needed to accurately predict actuator loads to replicate joint loads demonstrating there is a distinct improvement that can be made over this method.

In-Vivo Loads Used in Current Research

With the recent advent of the instrumented tibia the data has been used for a number of purposes. The profiles have been used as a target for wear simulators and Reinders et al. have developed a wear testing protocol using these joint loads [24]. The authors used a three-degree-of-freedom simulator which allowed for knee motion in F-E, A-P and I-E. A procedure was developed that cycled between five different loading conditions to replicate the typical use of an implant and determine the effect of wear from each activity. These results demonstrated the ability to adapt these loads into an effective in-vitro simulation.

Chapter 3: Replication of Physiological Loading at the Knee Joint for an Oxford Style Knee Simulator Using a Neural Network Approach

Introduction

In-vitro simulations of in-vivo activities are an invaluable tool for studying the knee joint. In-vitro simulators allow for testing that would be impractical or unethical to perform in-vivo. These devices have been used for numerous analyses, including studies done on the natural knee [25], injured knee [6], and prosthetics [4]. These in-vitro simulator studies have been used for the characterization knee motion and laxity [5], analysis of the mechanics of injury [6], evaluation of total knee prosthetics prior to in-vivo implantation [4], and many others. Typically these studies use a consistent loading condition at the joint for each trial, reducing test variation in comparison to in-vivo testing. In order to replicate in-vivo joint loads, a wide variety of knee simulators have been developed. Oxford-style knee rigs, such as the Kansas Knee Simulator (KKS), are one of these in-vitro simulators that has found success replicating in-vivo conditions [17]. While many configurations exist, Oxford-style rigs classically allow complete six-degree-of-freedom joint motion with the hip situated directly above the ankle [26]. The femur and tibia are secured to the machine and loads can be applied to both bone ends as well as to the musculature. While these studies have related simulators, the loading conditions at the joint used have varied between studies and careful planning must occur when determining an appropriate joint loading condition to target.

One way joint loading conditions were determined was the use of musculoskeletal models using force plate data [9-11]. The use of force plate data coupled with these models created joint loading predictions, but the predicted loads were imprecise as wide variation was seen between loads for the same cycle [10, 11], limiting their usefulness as targets for knee simulators. The advent of the instrumented tibia has provided a more direct and reliable insight into joint loading conditions [12, 13]. The instrumented tibia allows for direct collection of joint loads in a prosthetic knee during activities of daily living (ADLs) that were previously calculated from force plate data. These include walk cycles, deep knee bends, stair ascents, and chair rises, to name some common activities. These data provide detailed representation of joint loads throughout ADLs which provides an opportunity to match physiological joint loads in-vitro.

In order for an in-vitro simulator to reach target loads an actuator loading profile must be created for the in-vitro simulator. Oxford-style rigs were traditionally designed with force plate data in mind; each axis that acts on the tibia contributes in a way that allows for direct feedback from force plates to the simulator. Forces were read at the foot, so actuator loads can be applied using the ankle. This led to multiple axes from both the hip and ankle being used to control the sagittal plane loading conditions, which can result in coupling between axes. For example, the KKS relies on three actuators to drive sagittal plane loads: a moment about the ankle flexion-extension axis, a vertical force on the hip, and a force directed on the quadriceps [17]. This coupling creates difficulties in reaching desired sagittal plane loads directly at the joint as each axis contributes in both the superior-inferior (S-I) and anterior-posterior (A-P) directions. The effect of each actuator on joint loads varies as the knee moves throughout the flexion cycle. This creates a need to cross-compensate between axes when controlling the system, making simple control, where each axis is responsible for one joint load direction, impractical. To effectively utilize the improved in-vivo data a more substantial effort is needed to determine the actuator loading profiles required to replicate physiological joint loads.

The goal of this study was to develop and validate a method for determining actuator loading conditions needed to replicate in-vivo joint loads in an Oxford-style knee simulator. The specific aim of this study was to use a neural network to predict the actuator loading profiles necessary to replicate a walking cycle's joint loads derived from in-vivo data. Once completed it is hoped that this method can be used to generate more complex loading conditions at the joint and allow for a wide range of future research.

Material and Methods

The KKS is a five-axis servo-hydraulic Oxford-style dynamic knee simulator. Like many other Oxford-style rigs, the KKS allows for the application of loads to the joint while allowing the knee to be unconstrained in all six kinematic degrees of freedom. There are five axes of control in the KKS (Figure 1): quadriceps force (QF), vertical force (VF), ankle flexion (AF), tibia torque (TT) and an abduction-adduction (AA) sled. These axes are slightly different than in the literature as changes were made to the simulator as specified in Appendix B. The QF actuator pulls on the quadriceps head and is typically run in position control guiding the knee to the desired hip flexion angle. Both the VF and AF actuators are in the sagittal plane and contribute to the superior-inferior (S-I) and anterior-posterior (A-P) loading at the joint. The VF produces a load vertically at the hip and the AF actuator creates a flexion-extension moment about the ankle. The final two actuators drive out-of-sagittal plane loads. The AA sled applies medial-lateral (M-L) load at the ankle causing a varus-valgus (V-V) moment at the knee. The TT actuator creates a moment about the long axis of the tibia and induces an internal-external (I-E) moment at the joint. The knee is fixed to the simulator with the femur fixed to the hip and the tibia fixed to the ankle. The hip is situated above the ankle and the system allows for a full six-degrees-of-freedom at the knee. Under consistent loading conditions kinematic differences can be observed between specimens or conditions due to differences in factors such as geometry and soft tissue.

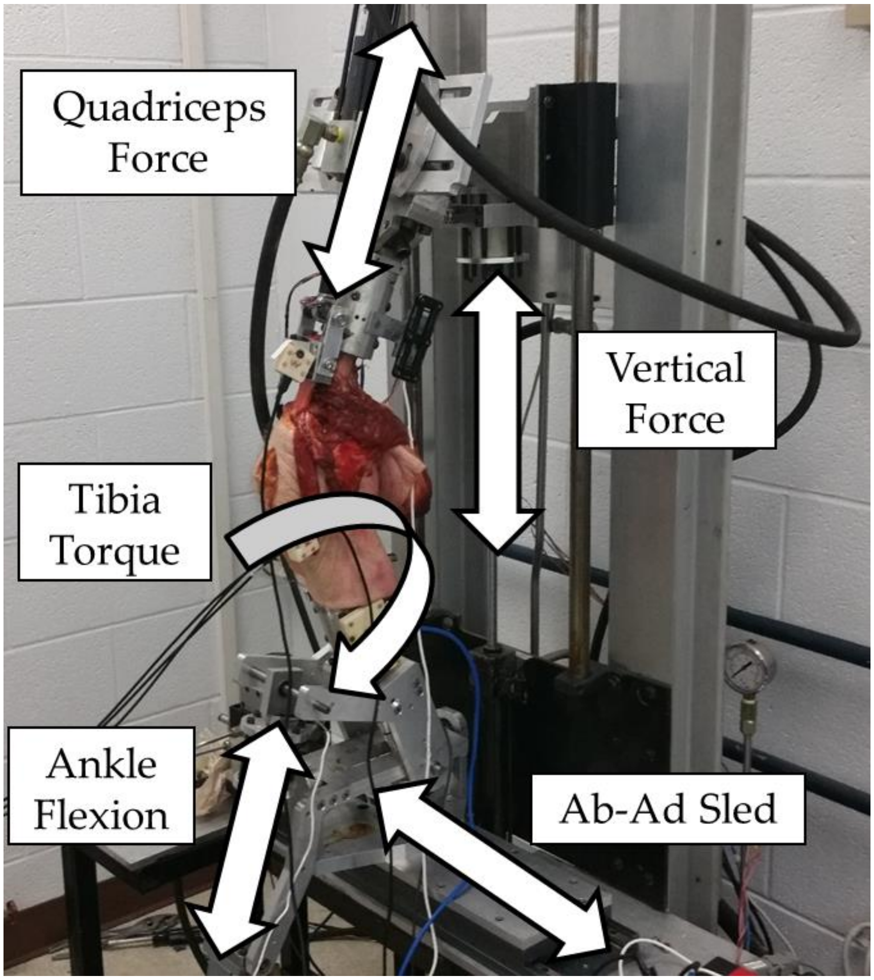

Figure 1: KKS Axes of Control

Each axis of the KKS has an individual PID controller used to control the system. Each of the five actuators' individual PID control parameters have been manually tuned to provide the best possible system response during representative dynamic simulations. Axes are typically tuned individually while coupled axis are cycled. For example, when tuning the VF actuator there are two additional actuators that impart motion in the same plane, the QF and AF actuators. The QF, VF, and AF actuators are all cycled through representative profiles while the VF's PID values are adjusted. As the tuning improves the tracking error caused by the interaction of competing actuators is compensated for, allowing for improved tracking in the desired direction. When the coupling becomes too great, which typically occurs with the QF actuator as it is responsible for flexion, cross compensation may be used. This cross compensation is enabled for the AF actuator. The hip angle, determined by the position of the QF actuator, is used in the AF PID control to allow for changes in tuning through the flexion range. The tracking of the actuators was analyzed by comparing the target and measured value for each actuator and calculating the relative RMS. The relative RMS error was 0.32 in QF, 0.28 in VF, and 0.35 in HA indicating acceptable tracking.

An implantable instrumented tibia tray was designed by Chadd Clary of DePuy Synthes Joint Reconstruction. The tibia was a modified version of a Size 8 Attune Tibial Base, with a cavity induced in the proximal surface of the tray (Figure 2). The tray was divided into three sections: medial, central, and lateral with each section housing a piezo-electric tri-axial load transducer capable of measuring of three axes of force. The exact location of each force measurement was known allowing for the calculation of all three forces and three moments that occurred at the joint.

Figure 2: Instrumented Tibia Tray

For this study, targeted loading conditions for testing were developed based on data from the OrthoLoad database [12]. The AVER75 walk was used as a basis for the profile with some modifications to allow for constraints of the simulator and implant used in this study (Figure 3). Due to the low compression throughout swing phase, instability can occur. To prevent this, a conservative minimum allowable compression of 250 lbs. was used to ensure no dislocation or other non-physiological effect would occur throughout the cycle. The implant in this study was less conforming than the implant used to generate the OrthoLoad data, to account for this difference A-P loads were reduced to 50% of the reported loads. The reduced conformity typically means than the Orthoload database reducing the amount of loading other than compression compensated for by the implant. No out-of-sagittal plane loading was considered in this study. The AA and TT actuators were held at zero load throughout the cycle. To demonstrate the change that occurs due to cycle time, two profiles were created with identical target loads and different periods. The slow walk had a period of twenty seconds and the fast walk had a period of ten seconds.

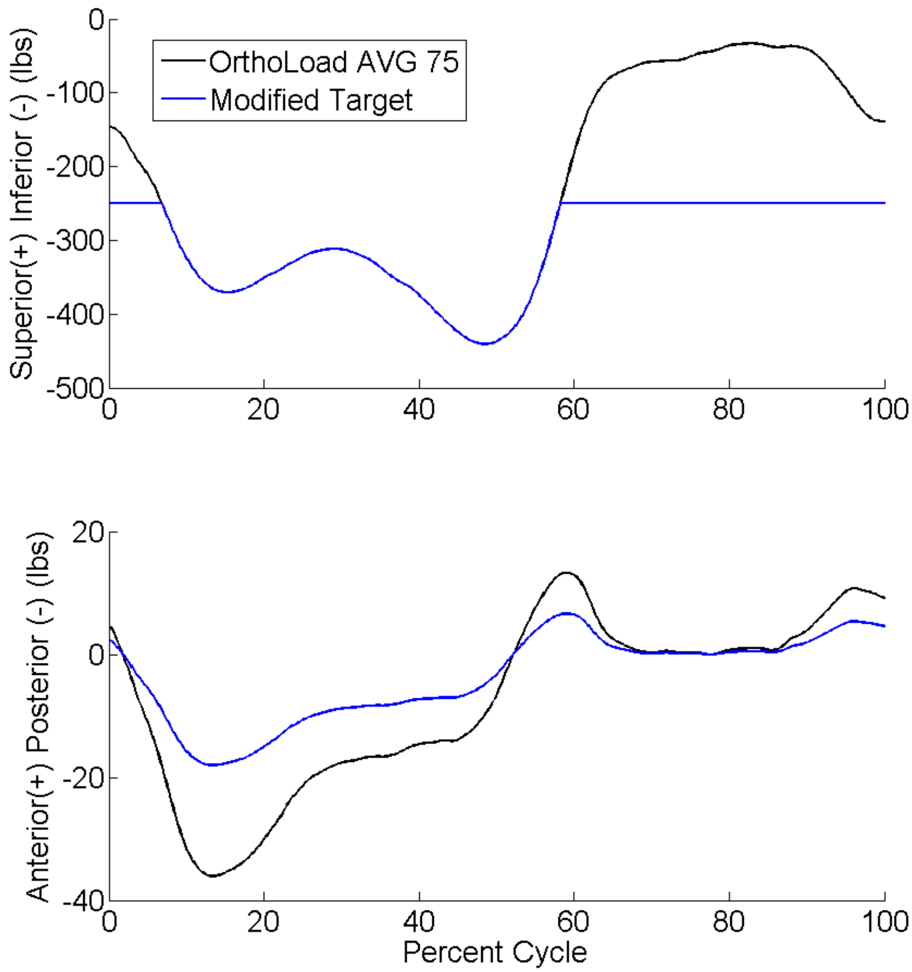

Figure 3: Target Joint Loading Conditions

To analyze the performance of the profile generated, a comparison was made between the target and generated profile to the difference between OrthoLoad's individual walk cycles to the average walk cycle. It can be assumed that by producing a walk cycle that has a root mean square (RMS) error to the target that is within the range of the average RMS deviation between an individual and the average the walk cycle has shown itself to be within the physiological range of a walk. When comparing the eight walk cycles that are used to create the average walk cycle in the S-I direction, an RMS deviation of 38.3±20.2 lbs. was found. The A-P direction of each individual walk cycle to the average had an RMS deviation of 7.1±2.7 lbs.

A neural network was developed to predict the necessary actuator loading profiles to reach target loading conditions at the joint. Using Matlab's Neural Network Toolbox a two-layer feed-forward network was produced using four inputs, one hidden layer consisting of ten neurons, and two outputs (Figure 4). The inputs used were hip angle, angular velocity of the hip angle, total S-I loads at the joint, and total A-P loads at the joint. Outputs of the network were AF and VF.

One layer of ten neurons proved sufficient for the network to determine a solution to the problem, adding more neurons simply increased computing time without improving performance. Both the inputs and outputs are scaled to a range of -1 to 1 to prevent error due to differences due to the magnitude of loads between each input and output. A tan-sigmoid transfer function was used in the hidden layer and a linear transfer function was used in the output layer. To train the network training was accomplished using the Levenberg-Marquardt algorithm which was able to produce results of the required accuracy. When training the network, seventy percent of the data was used directly for training, fifteen percent was used for validation during the training process, and fifteen percent was used as an independent measure of performance after training. Performance was analyzed through calculating the mean squared error of the validation data set at each iteration. Training was stopped if the method failed to improve the validation checks six consecutive times.

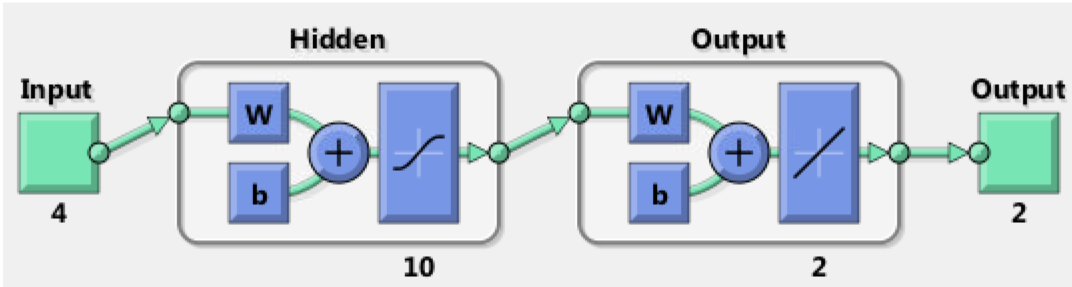

Figure 4: Neural Network Diagram

In order to generate profiles using the neural network, it must first be trained. First, the loading conditions at the maximum and minimum values in the cycle for hip angle, S-I, and AP were extracted from the targets (Table 1). This gave a total of six points from the target profile that would be used to develop a training set for the neural network. These points were chosen to ensure that the training data encompassed the target loads seen throughout the cycle. This allows for the neural network to interpolate between training data points for production rather than having to extrapolate. To determine the necessary actuator loads to reach these target joint loads, the instrumented tibia on the KKS. Actuator values that produce each of these six extreme points were found by manually adjusting the actuator values until the unique configuration that replicated the target static knee loads were found. Next, simple sine wave profiles were generated for the KKS that cycled loads between each pair of extreme points, giving a total of three cycles that are fed into the neural network for training. After the neural network has been trained, the target profile is fed into the network, producing predicted AF and VF actuator values needed to reach the target loads. This profile was then run on the KKS producing an RMS error of 83.5 lbs. in S-I and 6.2 lbs. in A-P. This was outside of the target RMS error, so to further improve the neural network performance this cycle was added to the training data and the neural network was retrained. This retrained data produced an RMS error of 23.4 lbs. in S-I and 3.8 lbs.

in A-P, within the target range so training of the neural network was stopped and the actuator loading profile generated was used for analysis in this study. The neural network generated was a near perfect fit to the data with the test case having an R value of .9964 (Figure 5).

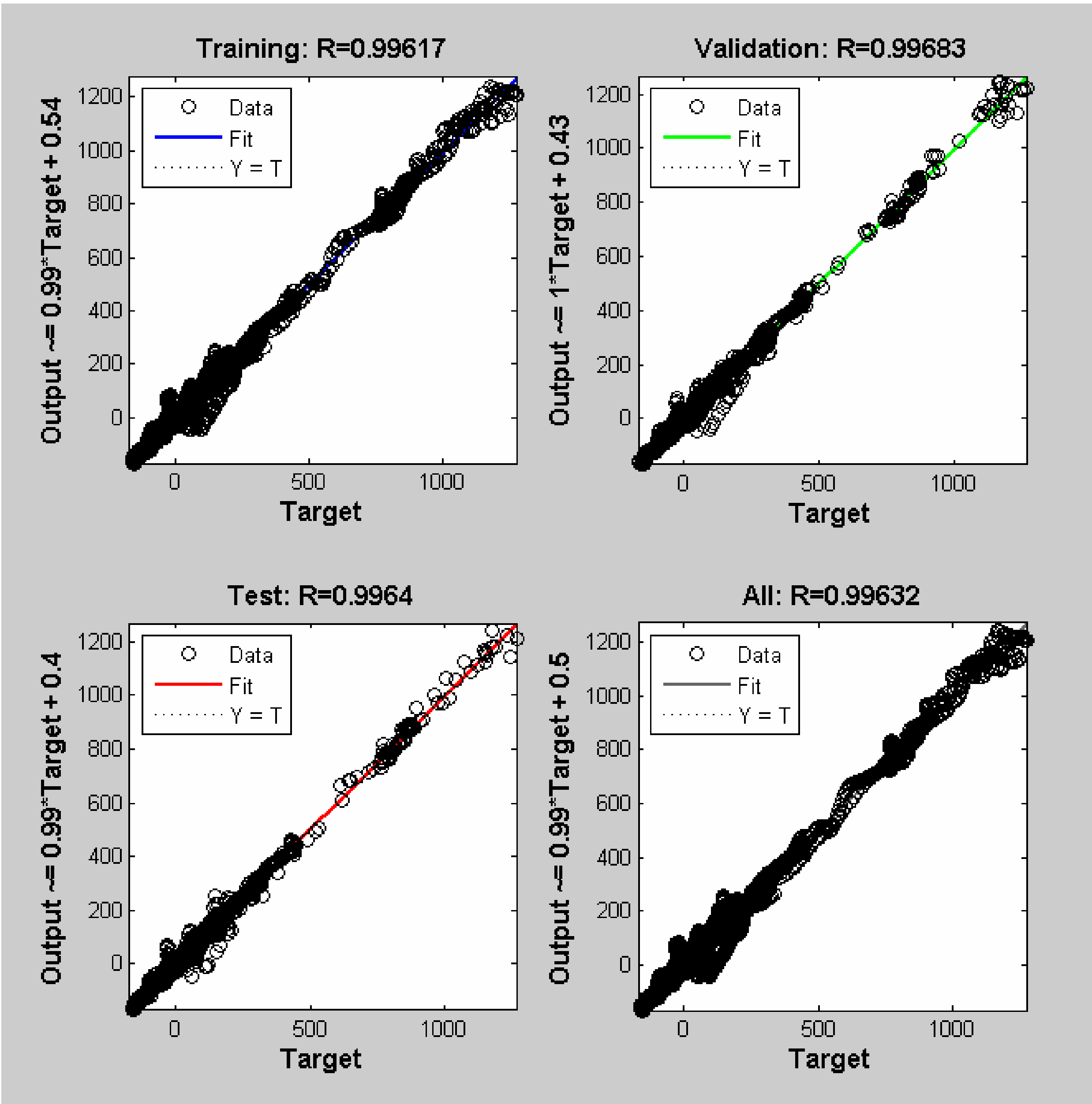

Figure 5: Regression of Neural Network

	HA	S-I (lbs)	A-P (lbs)
Min S-I	7.1	-440.7	-28.2
Max S-I	24.6	-250.0	0.6
Min HA	3.6	-250.0	-6.0
Max HA	31.1	-250.0	0.0
Min A-P	7.2	-440.6	-28.3
Max A-P	10.8	-369.0	10.8

Table 1: Sample Targets for Neural Network Training

Two cadaveric specimens (both male, age 69 and 57, BMI 28.1 and 16.5) were used in this study. The first specimen was used for training the walk cycle, while the second was used for verification of the profile produced. The cycle that was run on the specimen that was used for training is referred to as the training knee. The cycle run on the specimen where the training did not occur is referred to as the verification knee. These specimens were dissected with the bones cut 8.5 inches proximal and 7.5 inches distal to the epicondylar axis of the knee. The soft tissue on either side of the joint was left intact within 5.5 inches on the proximal side and 4.5 inches on the distal side of the joint. Aluminum fixtures were placed on each end and secured using bone cement. The rectus femoris and vastus intermedius were isolated and secured via sandpaper and superglue to a clamp to be used in the QF actuator by the KKS. A surgeon performed a total knee arthroplasty and implanted the instrumented tibia for use throughout the study.

Results

The derived slow walk cycle showed excellent agreement throughout the cycle on both the training and verification knees (Figure 6). The training knee had an RMS error of 23.4 lbs. in S-I and 3.8 lbs. in A-P (Table 2). The verification knee had an RMS error of 31.7 lbs. in S-I and 7.5 lbs. in A-P. The same loading profiles were run on both knees, but the verification knee's loads were slightly shifted both inferiorly and posteriorly when compared to the training knee. This shift improved agreement throughout much of the cycle in the S-I direction, but moved the A-P loads slightly away from the target.

	RMS	
	S-I (lbs)	A-P (lbs)
Ortho Average	38.3	7.1
Slow Training	23.4	3.8
Slow Verification	31.7	7.5
Fast Training	25.6	11.9
Fast Verification	32.4	12.0

Table 1: RMS error of loading conditions compared to orthoload walk average

The fast walk also showed good agreement, but was not quite as accurate as the slow walk was (Figure 7). The training knee had an RMS error of 25.6 lbs. in S-I and 11.9 lbs. in A-P. The verification knee had an RMS error of 32.4 lbs. in S-I and 12.0 lbs. in A-P. Again this profile showed good agreement in the S-I direction, but in the A-P direction a swift drop posteriorly occurs just after the midpoint of the cycle for both knees. The loads in the A-P direction then surpass the desired loads anteriorly before settling back towards the target. The verification knee follows the same trends as the training knee for the fast walk.

Comparing the training and verification profiles to the target values gives results similar to the values calculated from the individual Orthoload profiles. The training knee's RMS values are smaller in almost every instance when compared to the verification knee. The RMS of S-I to the average for all four cycles was smaller than the average RMS error of the eight individual OrthoLoad cycles to the OrthoLoad average. In the A-P direction the slow walk RMS values were approximately equal to the RMS seen from the Orthoload averages. The fast walk RMS values were slightly higher, but were within 2 standard deviations of the RMS walks seen.

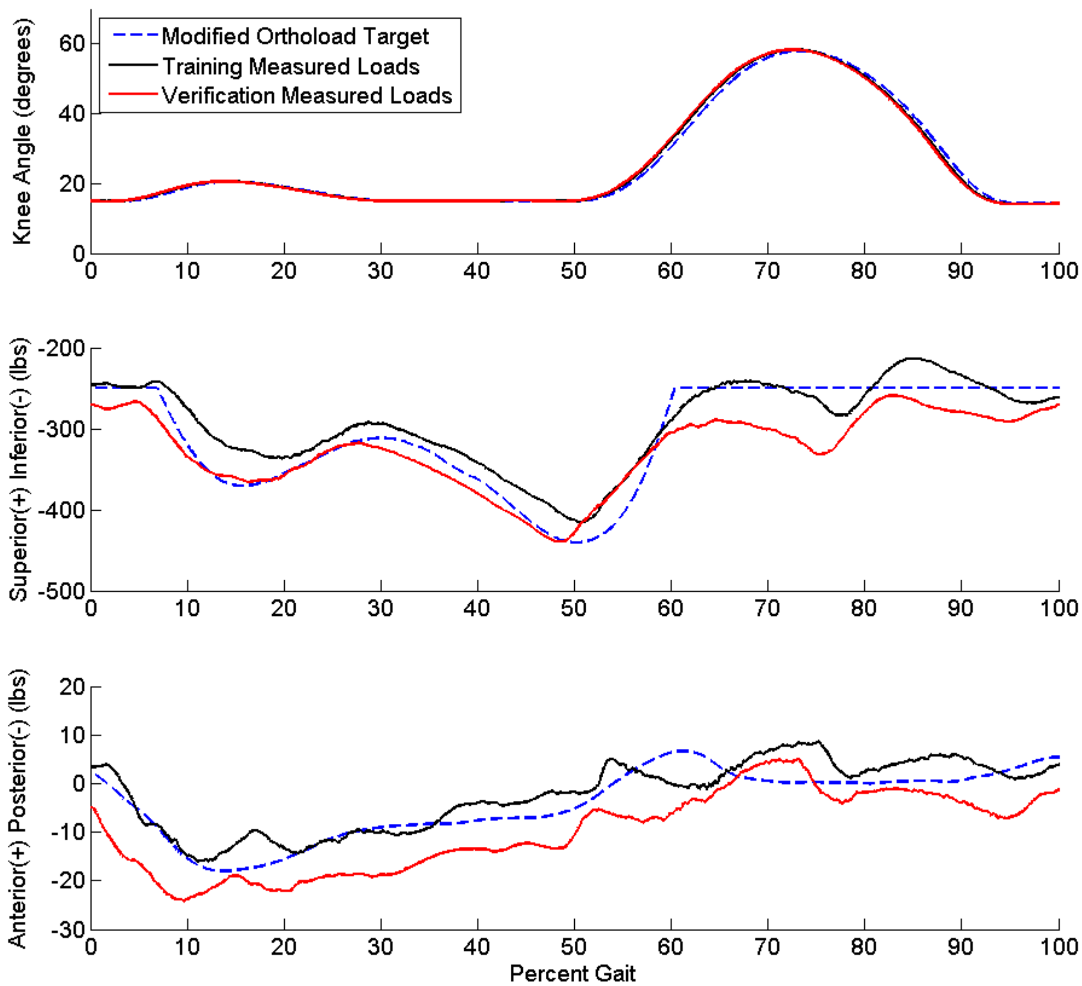

Figure 6: Slow Walk (Period of 20 Seconds)

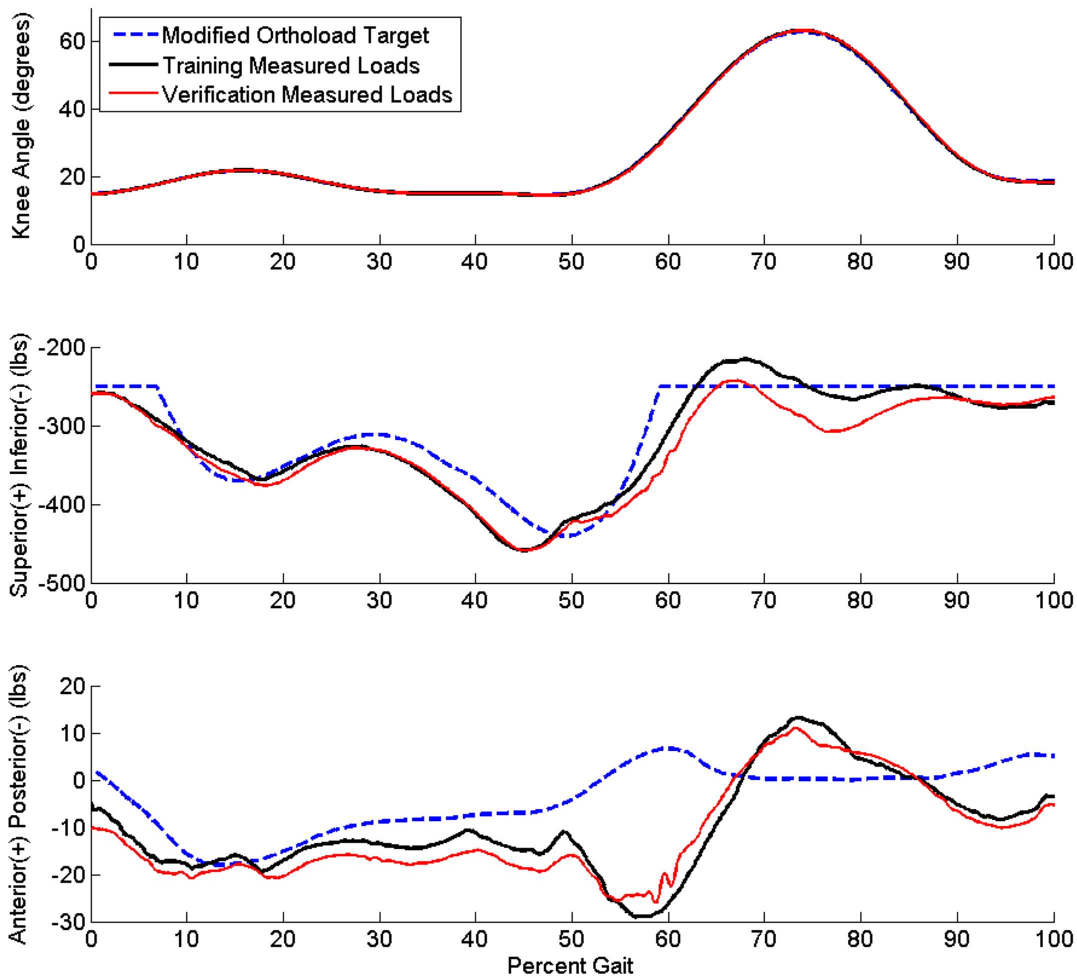

Figure 7: Fast Walk (Period of 10 Seconds)

Discussion

The results suggest that there is good agreement between the target loads at the joint and the measured loads, indicating that the walk cycle produced is physiologically relevant. The RMS error of the generated profile is comparable to the inherent differences of natural human gait seen by the RMS differences of the OrthoLoad individual cycles to the average. The S-I loading RMS error was lower than the difference between the individual cycles and the average indicating that the compression is definitively physiological. The A-P loading was slightly higher than the average for the fast walk, but was within the limits for the slower profile.

There is a limited time during which the profiles fail to match the A-P target load, and this is just after the midpoint of the walk cycle. The most likely cause of this error is due to error in the tracking of the KKS (Figure 8). The tracking of the KKS to the predicted profile matches up until the same region that the A-P loads match. Further analysis shows that there is a clear correlation between the two errors (Figure 9). A trendline demonstrates an r squared value of .802 indicates a strong relationship between the two errors [27]. It can be theorized that by improving the tracking of the simulator for the ankle flexion axis, the loads at the joint will similarly improve and allow for a more controlled physiological A-P load for the entirety of the cycle. As the tracking issue is apparent for the faster walk and not the slower walk, the inertial effects are likely changing the plant throughout the cycle. An investment in developing improved PID values for the AF actuator will need to be undertaken to improve the tracking of this axis and therefore the reliability of the profiles created by this neural network method.

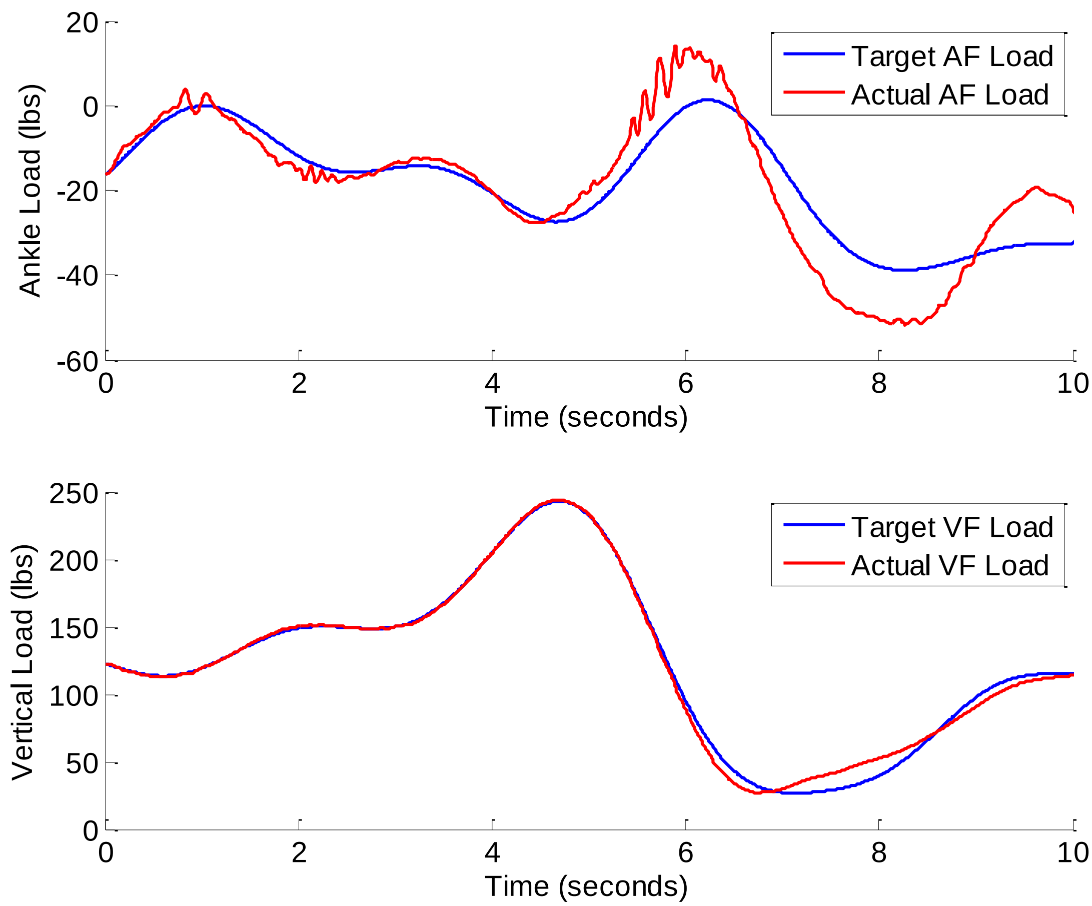

Figure 8: Tracking for Fast Walk Cycle of Verification Knee

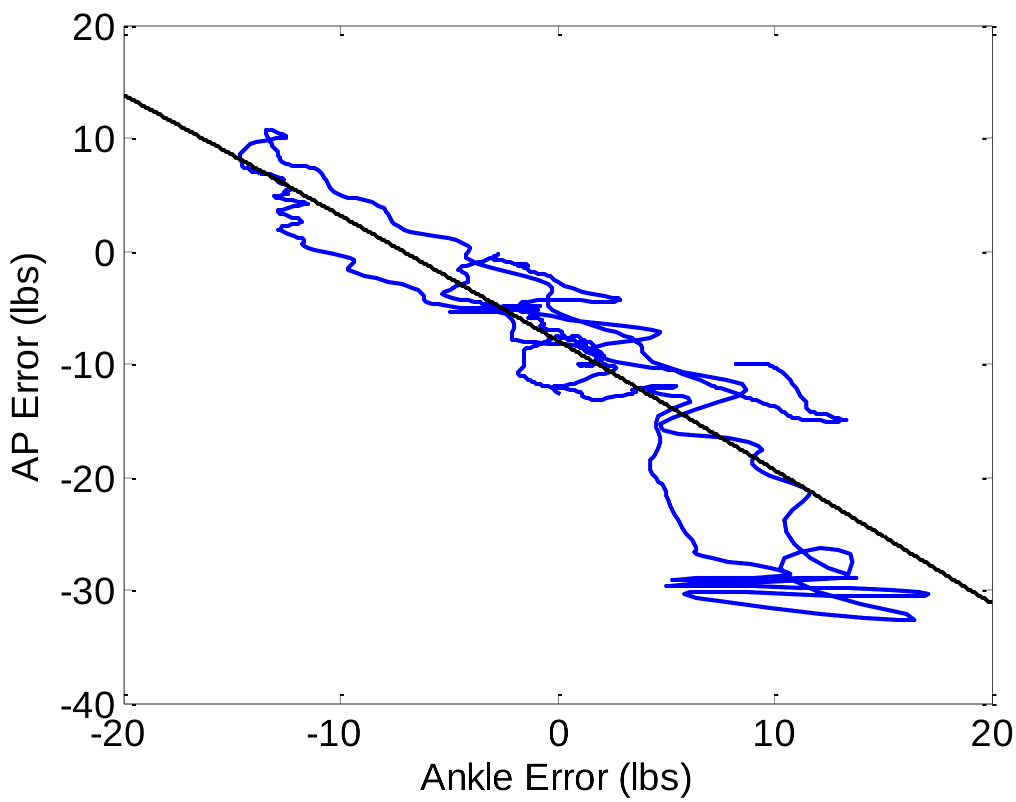

Figure 9: Ankle Flexion (AF) Error vs A-P Error for Fast Walk of Verification Knee

Line fit R^2 = .802

There are other methods that can be used to generate input loading profiles to produce physiological loading conditions. One such method is a dynamic rigid body model of the system (e.g. using Adams MSC). By recreating the KKS in Adams and running a co-simulation with Matlab and Simulink a predictive tool was created that allows for prediction of necessary actuator loads to recreate the loads at the knee [14]. There are some benefits to this method, such as the ability to create profiles for simulator configurations that do not currently exist. However, the model has proven to be sensitive to slight adjustments in position and configuration of the model simulator reducing the ability of the researcher to match the loads at the knee between the model and the physical simulator. This difficulty has currently prevented the creation of a loading cycle that is testable within the KKS. Other methods that are more similar to the neural network have also been tried such as a Kalman Filter based state space model of the system (Appendix A). This method worked similarly with a training data set that would then be used to predict the profile, but this state space approach lacked the consistency found with the neural network.

In addition to changes caused by the implant design, there is an inherent difference from soft tissue, implant alignment, and other factors. These differences can cause changes of the loads at the knee despite consistent external loading conditions and consistent implant design. While not controllable, it is expected that the difference in measured loads at the knee using consistent loading conditions will remain within the seen physiological range which has been shown in the results so far. In this study, the RMS error between the same cycle on two different specimen was 24.1 lbs in S-I and 2.9 lbs in A-P. This is within the difference between individual cycles, but due to a lack of data no real conclusion can be drawn about the consistency from specimen to specimen. More trials with the instrumented tibia are necessary to demonstratively show that the inter-specimen variation is within the correct physiological range.

With the difficulties of keeping consistent loads from knee to knee, determining a proper target profile becomes increasingly difficult. Average cycles are useful as a starting point, but they are not representative of any individual's particular loading condition. When determining a loading condition to use, evaluating the source along with the purpose is vitally important. Many ADLs, such as walks, have profiles that remain relatively consistent between subjects. Other ADLs, such as deep knee bends, have large variability between every subject. For cycles that are similar between subjects using the average as a target is likely a good representation of the population.

For other cycles the average likely isn’t as good of a representation so specific patients may serve as a better target. An analysis should be performed on potential target data to determine the best targets for individual ADLs. Targets should be chosen based on the purpose of testing, for example if trying to replicate injury conditions extreme loading values should be used as they are most likely to be the cause of injury. In wear simulation body weight should likely be increased from 75 kg to 100 kg to ensure that the more extreme end of the profile is considered as more extreme loads will likely be the cause of wear.

There are a number of limitations to this study. As discussed previously, loading conditions are derived from a different prosthetic than was used to reach the target loads. This can cause a change in behavior of the observed loads at the knee joint. In addition, the instrumented tibia used for this study is not always available for use; profiles need to be created so they can be used without the instrumented tray. In addition, the results are only valid during the stance phase of the cycle as the targeted loading conditions during swing phase were not physiological. In addition, a limited number of specimen have been used to qualify results. This limited number of specimen makes it nearly impossible to get true statistical significance out of the data. While I do not believe that the results will drastically change after adding more specimen, more trials will need to be run to have statistically significant results.

Chapter 4: Conclusion

The neural network approach showed promise as a useful tool for generating loading profiles that replicate in-vivo joint loads. Through cadaveric research a walking profile was developed that closely matched a target cycle with an RMS error ranging from 23.4 to 32.4 lbs in the S-I direction. The joint loads fell within the range of physiological variation seen in the OrthoLoad walk cycles, an RMS of 38.3 lbs. in S-I. This method is not without faults, but it has been most successful at producing useful profiles of all the methods tested and appears to have a few routes towards even further improvement.

While this method worked well for a walk cycle, physical limitations of the cadaveric specimens prevented testing the method for more extreme cycles such as a deep knee bend. There are a number of limitations of the KKS, one of which is quadriceps tearing when the quadriceps is held at too high of a load for an extended period of time. Due to the setup of the KKS and the nature of a deep knee bend, the QF actuator reaches loads in excess of 2000 N during deep flexion. This typically is not an issue during a normal cycle as little time is spent with the quadriceps load exceeding 2000 N; however, when a training data set is derived more extreme points are typically held for a longer period of time. This combination has led to quadriceps tears and limits the effectiveness of the method for higher loading conditions.

To prevent these issues that are associated with cadaveric work, a method that replaces the cadaver with only prosthetic components would work for prediction as long as the fixtures match cadaveric loading conditions. This prosthetics only setup avoids the pitfalls of cadaveric testing including degradation of tissue and changes that may occur in the soft tissue due to overloading. One of the biggest advantages of prosthetics only over cadaveric training is an improved range of loads that can be applied to the joint as the prosthetics can be subjected to more extreme loading conditions without breaking. Through avoiding these issues with training cadavers, this method has a much greater likelihood of success for creating a robust training data set. Many more profiles can be created without worry of tearing the quadriceps muscle or changes in the knee causing a poor model prediction. As this project moves forward, it is recommended that this route be taken to continue making progress with the neural network.

Determining proper target loads is a major challenge facing any method that aims to replicate physiological joint loading conditions. There are many factors that affect loads at the knee including bone morphology, ligament structure, and body weight. While determining joint loading conditions has improved with the advent of the instrumented tibia, it is not without faults. The loads that are collected are a small subset of the population. All patients were osteoarthritis sufferers who had a total knee arthroplasty performed and a particular implant designed specifically for collecting loads. While these loads are accurate, they only represent the loading conditions found with this particular set of implants. Simple changes in the morphology of the implant creates differences in loads that are difficult to accurately predict.

One of the major dependencies of this method is the training data set that is supplied to the neural network. As specified in the methods section, the neural network used contains four inputs and two outputs. In order to get reliable results, the training data set needs to provide loading data surrounding the range that is needed for the target profile. Individually this is not a challenge, but reaching the correct loads in conjunction is complicated. Due to the high degree of coupling between the VF and AF actuators, the contribution of both actuators changes throughout the range of flexion. Even if data is collected for training that contains the range of S-I and A-P that is necessary for the target that does not necessarily mean that the neural network will be able to predict the correct profile. These changes need to be accounted for and training data needs to be collected that encapsulates the proper S-I, A-P, and flexion angle that will be used in the target. The method used for training in this study was to manually cycle between the maximum and minimum points of the proposed cycle. This works well for a walk cycle, but as previously stated when the loading conditions become more extreme cadaveric specimen can fall apart. Using this neural network to predict a loading cycle that lies outside the range of the training data will likely lead to a very poor prediction. Understanding the limitations of the neural network is vital for using this method to predict profiles.

In addition, one more limitation of this method is it requires the use of the instrumented tibia tray. The creation of the neural network relies on access to the instrumented tibia to allow for the training data to be collected. Without the tray or a similar method to determine joint loads training data cannot be collected, and profiles created cannot be verified. To account for the possibility of limited availability of the tray a large training data set could be created to encompass the expected range of profiles that may be generated in the future. This would require a method to be created that determines whether the neural network generated has the proper training set to produce the target profile as there would be no way to verify whether the profile created was correct without the tray to measure joint loads.

While the S-I loads were well within the physiological range of variation the A-P loads were farther off. For much of the cycle the A-P loads matched closely, but at the midpoint they significantly deviated. This occurred during the start of a large flexion change with a significant drop in compression. This combination causes the prediction to have a quick shift in both the VF and AF actuator. While the KKS can reach the loads necessary there are occasionally hiccups in tracking. This is one of those times. The tracking of the simulator at this point is poor. While the VF actuator tracks about perfectly the AF actuator does not keep up. The AF actuator overshoots its intended target and creates unwanted posterior loads at 55% of the gait cycle and then passes the intended target again and creates overly anterior loads at 70% of the cycle. Any prediction method will not be able to properly account for this change in tracking and the neural network is no exception to this rule. By improving the tracking of the actuator the predicted output of the neural network will be much more likely to match the targets.

References

1. Services, U.S.D.o.H.a.H., *National Hospital Discharge Survey*, U.S.D.o.H.a.H. Services, Editor. 2010.
2. Kurtz, S., K. Ong, E. Lau, F. Mowat, and M. Halpern, *Projections of Primary and Revision Hip and Knee Arthroplasty in the United States from 2005 to 2030.* The Journal of Bone & Joint Surgery, 2007. **89**(4): p. 780-785.
3. Noble, P.C., M.J. Gordon, J.M. Weiss, R.N. Reddix, M.A. Conditt, and K.B. Mathis, *Does Total Knee Replacement Restore Normal Knee Function?* Clinical Orthopaedics and Related Research, 2005. **431**: p. 157-165.
4. DesJardins, J.D., P.S. Walker, H. Haider, and J. Perry, *The use of a force-controlled dynamic knee simulator to quantify the mechanical performance of total knee replacement designs during functional activity.* Journal of Biomechanics, 2000. **33**(10): p. 1231-1242.
5. Walker, P.S., S. Arno, I. Borukhoy, and C.P. Bell, *Characterising knee motion and laxity in a testing machine for application to total knee evaluation.* Journal of Biomechanics. **48**(13): p. 3560-3567.
6. Li, G., T.J. Gill, L.E. DeFrate, S. Zayontz, V. Glatt, and B. Zarins, *Biomechanical consequences of PCL deficiency in the knee under simulated muscle loads—an in vitro experimental study.* Journal of Orthopaedic Research, 2002. **20**(4): p. 887-892.
7. D'Lima, D.D., M. Trice, A.G. Urquhart, and C.W. Colwell, *Comparison between the kinematics of fixed and rotating bearing knee prostheses.* Clinical Orthopaedics and Related Research, 2000(380): p. 151-157.
8. Fitzpatrick, C.K. and P.J. Rullkoetter, *Estimating total knee replacement joint load ratios from kinematics.* Journal of Biomechanics, 2014. **47**(12): p. 3003-3011.
9. Lu, T.W., J.J. O'Connor, S.J.G. Taylor, and P.S. Walker, *Validation of a lower limb model with in vivo femoral forces telemetered from two subjects.* Journal of Biomechanics, 1998. **31**(1): p. 63-69.
10. Taylor, W.R., M.O. Heller, G. Bergmann, and G.N. Duda, *Tibio-femoral loading during human gait and stair climbing.* Journal of Orthopaedic Research, 2004. **22**(3): p. 625-632.
11. Wehner, T., L. Claes, and U. Simon, *Internal loads in the human tibia during gait.* Clinical Biomechanics, 2009. **24**(3): p. 299-302.
12. Bergmann, G., A. Bender, F. Graichen, J. Dymke, A. Rohlmann, A. Trepczynski, M.O. Heller, and I. Kutzner, *Standardized Loads Acting in Knee Implants.* Plos One, 2014. **9**(1).
13. D'Lima, D.D., S. Patil, N. Steklov, J.E. Slamin, and C.W. Colwell, *Tibial forces measured in vivo after total knee arthroplasty.* Journal of Arthroplasty, 2006. **21**(2): p. 255-262.
14. Guess, T.M. and L.P. Maletsky, *Computational modeling of a dynamic knee simulator for reproduction of knee loading.* J Biomech Eng, 2005. **127**(7): p. 1216-21.
15. Glitsch, U. and W. Baumann, *The three-dimensional determination of internal loads in the lower extremity.* Journal of Biomechanics, 1997. **30**(11-12): p. 1123-1131.
16. MacWilliams, B.A., D.R. Wilson, J.D. DesJardins, J. Romero, and E.Y. Chao, *Hamstrings cocontraction reduces internal rotation, anterior translation, and anterior cruciate ligament load in weight-bearing flexion.* J Orthop Res, 1999. **17**(6): p. 817-22.
17. Maletsky, L.P. and B.M. Hillberry, *Simulating dynamic activities using a five-axis knee simulator.* J Biomech Eng, 2005. **127**(1): p. 123-33.
18. Walker, P.S. and H. Haider, *Characterizing the motion of total knee replacements in laboratory tests.* Clinical Orthopaedics and Related Research, 2003(410): p. 54-68.

19. Kanamori, A., S.L. Woo, C.B. Ma, J. Zeminski, T.W. Rudy, G. Li, and G.A. Livesay, *The forces in the anterior cruciate ligament and knee kinematics during a simulated pivot shift test: A human cadaveric study using robotic technology.* Arthroscopy, 2000. **16**(6): p. 633-9.
20. Li, G., S. Zayontz, E. Most, E. Otterberg, K. Sabbag, and H.E. Rubash, *Cruciate-retaining and cruciate-substituting total knee arthroplasty: an in vitro comparison of the kinematics under muscle loads.* J Arthroplasty, 2001. **16**(8 Suppl 1): p. 150-6.
21. Rudy, T.W., G.A. Livesay, S.L. Woo, and F.H. Fu, *A combined robotic/universal force sensor approach to determine in situ forces of knee ligaments.* J Biomech, 1996. **29**(10): p. 1357-60.
22. Baldwin, M.A., C. Clary, L.P. Maletsky, and P.J. Rullkoetter, *Verification of predicted specimen-specific natural and implanted patellofemoral kinematics during simulated deep knee bend.* Journal of Biomechanics, 2009. **42**(14): p. 2341-2348.
23. Halloran, J.P., C.W. Clary, L.P. Maletsky, M. Taylor, A.J. Petrella, and P.J. Rullkoetter, *Verification of Predicted Knee Replacement Kinematics During Simulated Gait in the Kansas Knee Simulator.* Journal of Biomechanical Engineering, 2010. **132**(8): p. 081010-081010.
24. Reinders, J., R. Sonntag, L. Vot, C. Gibney, M. Nowack, and J.P. Kretzer, *Wear Testing of Moderate Activities of Daily Living Using In Vivo Measured Knee Joint Loading.* PLoS ONE, 2015. **10**(3): p. e0123155.
25. Lo, J., O. Muller, M. Wunschel, S. Bauer, and N. Wulker, *Forces in anterior cruciate ligament during simulated weight-bearing flexion with anterior and internal rotational tibial load.* Journal of Biomechanics, 2008. **41**(9): p. 1855-1861.
26. Zavatsky, A.B., *A kinematic-freedom analysis of a flexed-knee-stance testing rig.* J Biomech, 1997. **30**(3): p. 277-80.
27. Evans, J.D., *Straightforward Statistics for the Behavioral Sciences*. 1996: Brooks/Cole Publishing Company.

Appendix A

State Space Approach to Profile Prediction

This paper was prepared for ME790-Optimal Estimation on 12/12/2014.

Abstract

Generating proper knee loads on a dynamic knee simulator is crucial to accurately characterize the performance of total knee replacements. Generating actuator loading profiles is one of the most difficult and time consuming steps in achieving proper loads at the knee. Developing an accurate state space model through the use of a prediction error estimation method is a proven way to categorize difficult to measure systems such as dynamic knee simulators. Through the prediction error estimation method a state space model was determined for the Kansas Knee Simulator. The generated state space model shows does not perfectly match the validation data, but the trends of the prediction are consistent with the measured loads. The limiting factor of this study was the training data set that was used. By improving the training data set the state space model will likely be able to accurately predict knee loads given an input loading profile.

Introduction

Producing proper loading at the knee joint is considered to be the most important factor in evaluating the performance of a knee replacement [1,2]. One of the most common ways to produce the proper loads on a knee analog or a cadaveric knee specimen is through the use of a dynamic knee simulator. While there are many different dynamic knee simulators, one of the most often used is an Oxford Style Rig. Oxford Style rigs have a hip mounted directly above the ankle and allow for unconstrained kinematics at the knee joint [3]. These unconstrained kinematics allow for proper evaluation of the relationship between the loads and forces at the knee [2].

The Kansas Knee Simulator (KKS) is a dynamic knee simulator that is used to simulate many different loading profiles [1]. The KKS has five axes of control as shown in Figure 1. A loading profile is generated to attempt to replicate the loads found at the knee for a given dynamic activity. These activities can range from a simple squat, a walking cycle, to complicated cutting maneuvers as seen in sports. When the knee simulator is run in the configuration as shown knee joint loads can be evaluated for the input loading profile that is being run. This allows for the validation of the loading profile that has been run.

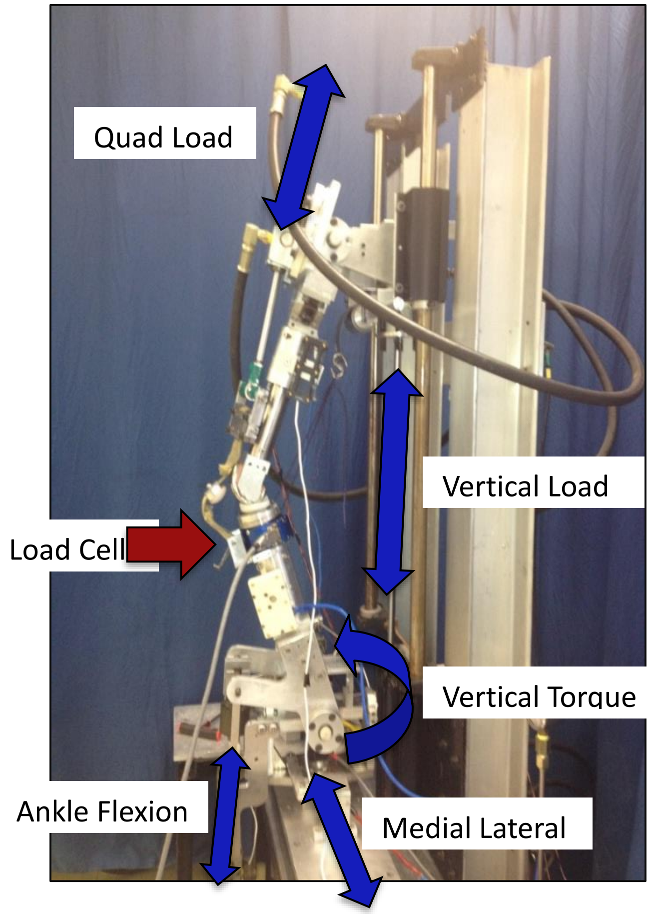

FIGURE 1: KANSAS KNEE SIMULATOR IN LOAD CELL CONFIGURATION

The KKS is controlled via an Instron (Instron, Norwood, MA) controller. Each axis of control has both a position and a load sensor to track the motion and load of the actuator. Typically the simulator is run with all but one axis in load control with the exception of the quad load which is run in position control.

One of the most challenging parts of running the KKS is the development of new loading profiles. The current setup calls for an iterative approach using a validated rigid body model (ADAMS MSC software) that has been developed to replicate the loads of the knee. The model is used to predict the needed actuator loads in the KKS to achieve the desired joint loads for a dynamic motion profile. The user inputs the desired loads at the knee to the model and a PID controller adjusts the actuator inputs through this control loop to match the simulated loads at the knee to the desired loads at the knee. This method tends to produce viable results, but only after time consuming manual tuning for each profile. There are variable factors in the KKS such as imperfections in the actuators and manufactured parts which cannot be easily modeled. While this model is a decent starting point, it doesn't completely achieve the goal of easily producing actuator loading profiles for the KKS.

Improvement of the profile generation method is a necessity in order to generate a wide variety of loading profiles. The first step is to develop a model of the system that accurately represents the loads at the knee given a set of actuator loading profiles. One common method for developing a model of a complex system is to use a prediction error estimation method. This method develops a state space model for a system using nothing but inputs and outputs from the system. This method is exceptionally useful for evaluating complex systems that are otherwise difficult to model [4].

The objective of this study is to use a prediction error estimation method to develop a state space representation of the KKS.

Methods

A set of equations to be used to describe the discrete system were established. The form is of a typical state space model with adjustable parameters θ.

$$x(t+1) = A(\theta)x(t) + B(\theta)u(t) + K(\theta)e(t) \qquad \text{Eq. 1}$$

$$y(t) = C(\theta)x(t) + D(\theta)u(t) + e(t) \qquad \text{Eq. 2}$$

Where A, B, K, C, D are all functions of θ which is set to be controllable parameters that the method will optimize. [5] The input to the system, u(t), is defined as the actuator loading profiles which consists of five inputs. The output of the system, y(t), is defined as the measured loads of the knee for a profile. The error in measurement is defined as e(t). For this application both the K and D matrixes are set to zero leaving the following system.

$$x(t+1) = A(\theta)x(t) + B(\theta)u(t) \qquad \text{Eq. 3}$$

$$y(t) = C(\theta)x(t) + e(t) \qquad \text{Eq. 4}$$

The next step needed for the solution is a prediction of both x and y. Based off the previous equations,

$$\hat{x}(t+1,\theta) = A(\theta)\hat{x}(t,\theta) + B(\theta)u(t) \qquad \text{Eq. 5}$$

$$\hat{y}(t+1,\theta) = C(\theta)\hat{x}(t,\theta) \qquad \text{Eq. 6}$$

where $\hat{x}(t+1,\theta)$is the next discrete estimated x value and $\hat{y}(t+1,\theta)$is the next discrete estimated y value. The error of the estimation can then be calculated.

$$\varepsilon(t_k,\theta) = y(t_k) - \hat{y}(t_k|t_{k-1},\theta) \qquad \text{Eq. 7}$$

Using this set of equations to calculate every $\hat{x}$ and $\hat{y}$ for the data set. Building on this an equation that can be used for minimization of the error can be developed.

$$Q_N(\theta) = \frac{1}{N}\sum_{k=1}^{N} \varepsilon(t_k,\theta)\, \varepsilon^T(t_k,\theta) \qquad \text{Eq. 8}$$

Q_N is the parameter that this method aims to minimize. As θ is varied Q_N should be lessened to provide a better fit to the data. This method uses a gradient that can be represented by

$$\varphi(t_k) = \frac{\partial \hat{y}(t_k | t_{k-1}, \theta)}{\partial \theta} \qquad \text{Eq. 9}$$

This gradient is then used to facilitate the minimization of Q_N. Many methods can be used to solve for the minimum such as Gauss-Newton, adaptive Gauss-Newton, Levenberg-Marquardt, gradient descent as well as a combination of all the mentioned methods. All methods mentioned are iterative approaches to determining the minimum of the sum squared represented by Q_N [6,7].

For this study the solution was found by running through the described method twice. The first pass started with a combination of the methods. For each iteration all four methods listed were calculated. The method that had the greatest decrease of Q_N was implemented for the step and again each of the four were calculated. After the first pass was finished the output system was fed into the full algorithm again setting θ to the initial state. The second iteration purely used the Levenberg-Marquardt method and converged to the final solution presented in the results.

A loading profile was chosen from a set of legacy data to be used as training for the prediction error estimation method as shown in Figure 2. The loading profile was generated using the Adams model of the system and aimed to replicate the joint loads found using an instrumented tibia[8]. The input profile was generated while trying to match loads only in the sagittal plane. The out of sagittal plane loads were ignored and both the vertical torque and medial lateral actuators were held at zero throughout the profile. The input profile contains three cycles of data

A different loading profile from legacy data was used as a validation of the state space

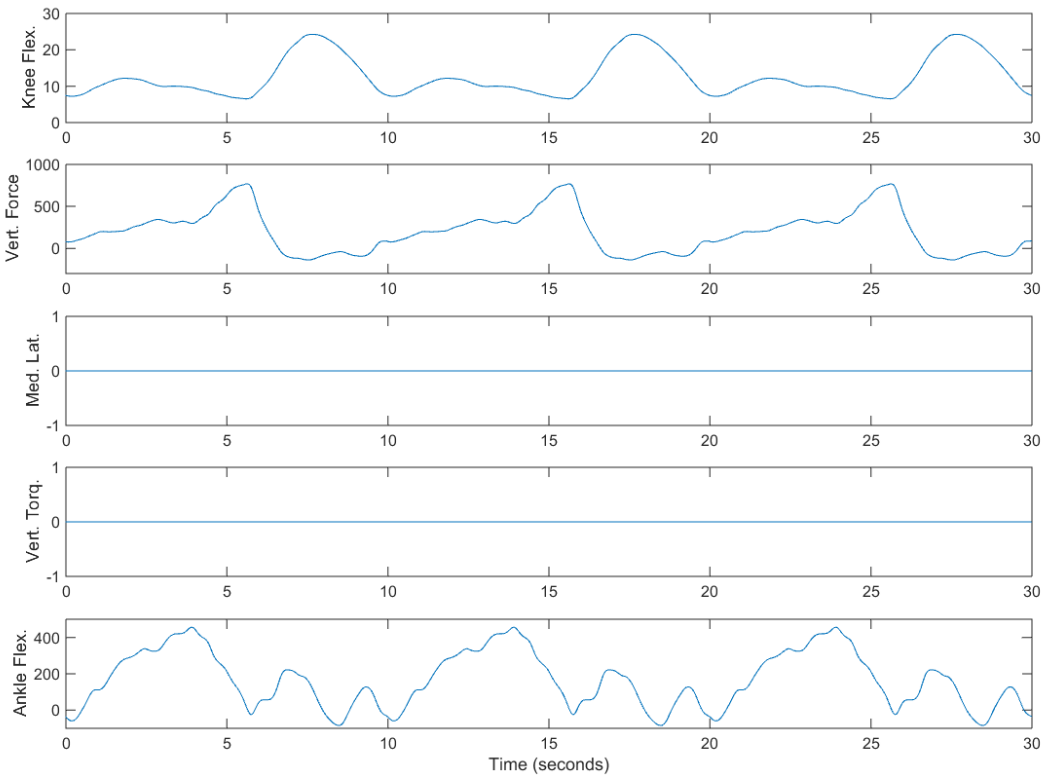

FIGURE 2: INPUT PROFILE DERIVED FROM D'LIMA WALK CYCLE

representation. The profile was developed using the Adams model based from ISO 14243-1 [9].

Results

The results of the training of the system are shown in Figure 3. Presented are the measured and predicted loads at the knee. There are three forces: medial-lateral (ML), anterior-posterior (AP), and superior-inferior (SI). There are three moments: flexion-extension (FE), varus-valgus (VV), internal-external (IE). The six loads were collected at 100 Hz and fully describe the loading at the knee.

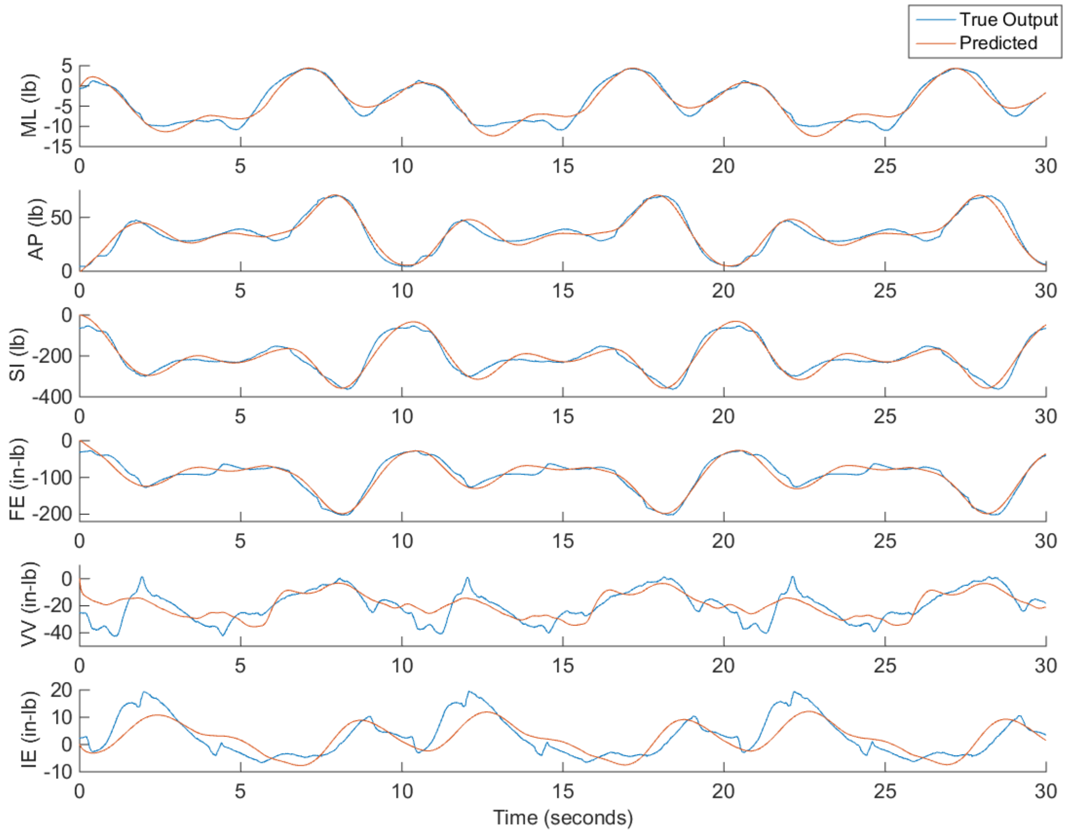

FIGURE 3: RESULTS OF TRAINING DATA

The results of the validation run are shown in Figure 4.

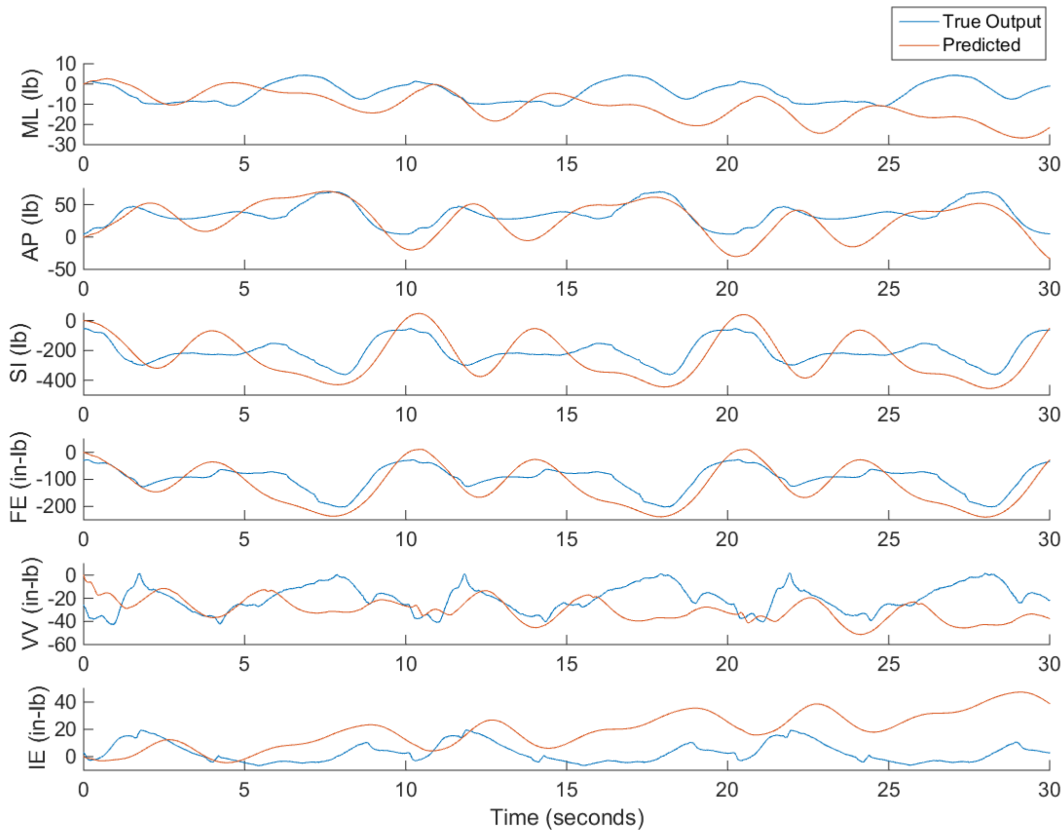

FIGURE 4 VALIDATION OF STATE SPACE REPRESENTATION

Discussion

The training profile shows good agreement between the state space model estimation and the actual output. ML, AP, SI, and FE all track closely. VV and IE do trend in the correct directions, but do not have as significant of a fit. This is likely due to the fact that the input profile does not intend to replicate out of sagittal plane loads. The input profile used has no actuator forces in either the medial lateral or vertical torque directions. These directions actuators are the ones that most directly influence the VV and IE forces. It can be reasonably assumed that if the training profile had incorporated all of the actuators the fit to the loading profile would be improved.

A modified version of the simulator will need to be used to collect addition training cycles as the KKS in the form that was used to collect this data no longer exists. Modifications to the KKS that allow for a greater range of profiles are currently being completed. At the time of this writing the revised simulator has been assembled, but has not been tested. As the simulator is brought back up and running one of the main goals moving forward will be to generate new loading profiles to simulate dynamic activities as all of the profiles currently defined will no longer be applicable. As the new profiles are defined the method described in this study the outcome will be compared to the modified version of the Adams model to determine which method or combination of methods will be best to generate loading profiles.

One of the largest improvements that can be made to improve the solution found through the presented method would be improving the training profile used. As mentioned previously, many limits exist with the profile used. A new profile could be developed purely for system identification. Included in this profile would be a complete set of data throughout the simulators full range of motion and load. There is a great deal of coupling that can be seen between actuators on the KKS which causes vastly different motion especially as the flexion angle changes. By developing a profile that changes loading conditions at a variety of flexion angles the prediction error estimation method will likely have a better data set to accurately train the model.

The physical modifications to the simulator should also assist in determining the state space. The modifications that have been made to the KKS are designed to decouple the VV and IE loads. Previously as the knee angle increased the VV and IE actuators were unable to influence their respective load without imparting a load on its counterpart. With the changes out of sagittal plane loads should be easier to produce and replicate on the simulator.

After improving the matching of the state space representation the next vital step is to create loading profiles using the improved solution. By using instrumented tibia data the necessary loads at the knee for many profiles are readily available. Prior to the modifications of the KKS the generation of profiles was a time consuming event using the model as previously described. Using the developed state space model should vastly reduce the amount of time it takes to complete profile generation.

Another possible area of exploration is evaluating the system using the tracking of the actuators to continue to improve the model. The presented method only considered the expected actuator loads. One possible way these could be used is to develop a better understanding of the physical constraints of the system. As the tracking changes the difference between the input and output profiles will drastically change. For example, if the PID values used to match the measured actuator loads to the inputs were to be changed the current model would not be accurate. The change in actual loads are not a part of the model, so as long as the input loads are the same the output loads will be predicted to be identical, regardless of tracking. By using the tracking as the input this situation could be partially avoided. The predicted input loads will be actual loads rather than input loads, but using the PID model the input loads could likely be extrapolated.

References

1. Maletsky, L.P. and B.M. Hillberry, *Simulating dynamic activities using a five-axis knee simulator*. Journal of Biomechanical Engineering-Transactions of the Asme, 2005. **127**(1): p. 123-133.

2. Walker, P.S. and H. Haider, *Characterizing the motion of total knee replacements in laboratory tests*. Clinical Orthopaedics and Related Research, 2003(410): p. 54-68.

3. Zavatsky, A. B. (1997). "A kinematic-freedom analysis of a flexed-knee-stance testing rig." J Biomech 30(3): 277-280.

4. Ljung, L. (1998). System identification: Springer.

5. Ljung, L. (2002). Prediction error estimation methods. Circuits, Systems and Signal Processing, 21(1), 11-21. doi: 10.1007/bf01211648

6. Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. Journal of the Society for Industrial & Applied Mathematics, 11(2), 431-441.

7. Gratton, S., Lawless, A. S., & Nichols, N. K. (2007). Approximate Gauss-Newton methods for nonlinear least squares problems. SIAM Journal on Optimization, 18(1), 106-132.

8. D'Lima, D.D., S. Patil, N. Steklov, and C.W. Colwell, *The 2011 ABJS Nicolas Andry Award: 'Lab'-in-a-Knee: In Vivo Knee Forces, Kinematics, and Contact Analysis.* Clinical Orthopaedics and Related Research, 2011. **469**(10): p. 2953-2970.

9. Flexion angles and cyclic duration are performed during wear simulations according to ISO 14243 under loading (ISO 14243-1).

10. MATLAB and System Identification Toolbox Release 2014b, The MathWorks, Inc., Natick, Massachusetts, United States.

Additional Thoughts on State Space Method

This method was the start for this thesis. While initially promising, there were a number of troublesome issues with the state space model that prevented it from creating profiles that were sufficient for physiological loading. The state space model was time dependent which caused the errors demonstrated in figure 4, as time went on the profiles tended to drift reducing the viability of the method. The neural network proves more useful as any set of target loads will output identical actuator loading conditions regardless of time of the cycle which is more reasonable.

Training also was difficult due to the same issues that were prevalent in the neural network, if the network is not trained to include the target loads the method would typically not be useful.

Appendix B

Redesign of KKS Ankle

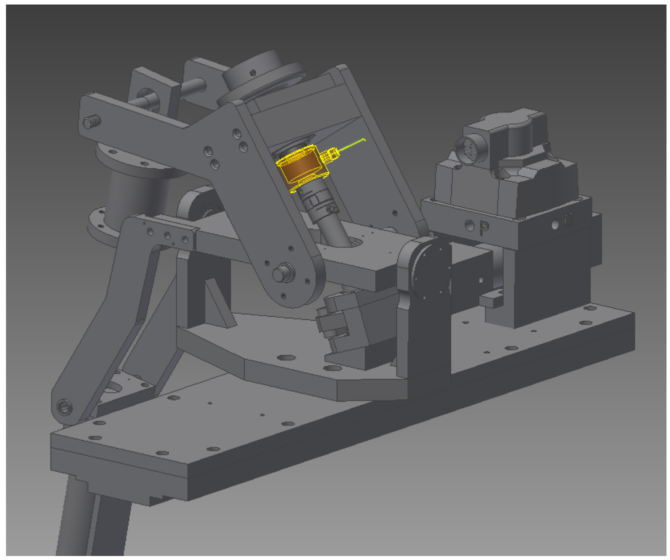

FIGURE 1: CAD MODEL OF KKS ANKLE REDESIGN

I also made adjustments to the KKS before I began on the topic of this thesis. The KKS has been modified to include an improved ankle flexion as well as an improved internal-external actuation.

The modified internal-external axis allows for a rotation about the long axis of the tibia rather than along a fixed vertical axis. This axis remains hydraulically actuated and will be monitored with a new torque sensor. The torque sensor was purchased through Interface and is capable of measuring torques up to 20 Nm. As shown in the Figs. 4 and 5, the torque sensor lies between a bearing constraint of the tibial fixture attachment and a flexible coupling designed for an allowance of any axial misalignment. This flexible coupling is connected to a universal joint that will transfer the applied torque throughout the full flexion range. There is currently no angular position sensor in this axis, although we may add the capability if the need arises. This axis will have the capability to rotate ±45° with a force of up to 18 Nm. This force and rotation should allow us to replicate any physiological internal-external rotation.

The modified ankle flexion axis is an improved version of the current setup. Currently there are a number of factors that limit the amount of force that can be transmitted through the actuator.

Changes were made to the attachment locations for the actuator creating a greater moment arm acting about the ankle. The current 8 ½” actuator was replaced with an actuator with a 10 ½” stroke length. This change allows for the same range of motion, but the increase makes up for the increase in moment arm. The former compliance mechanism, a rubber stopper, was replaced with a piston-cylinder system resembling the system on the vertical force axis. The system consists of a linear slide bearing fitted around a custom-made piston. On either side of the piston is a spring that will be used for compliance. By making these changes to geometry and compliance in the ankle flexion axis we will be able to exert forces in excess of 1000N in both directions. The knee system allows for flexion angles ranging from 0 to 130°. The load cell for the ankle flexion axis remained the same.

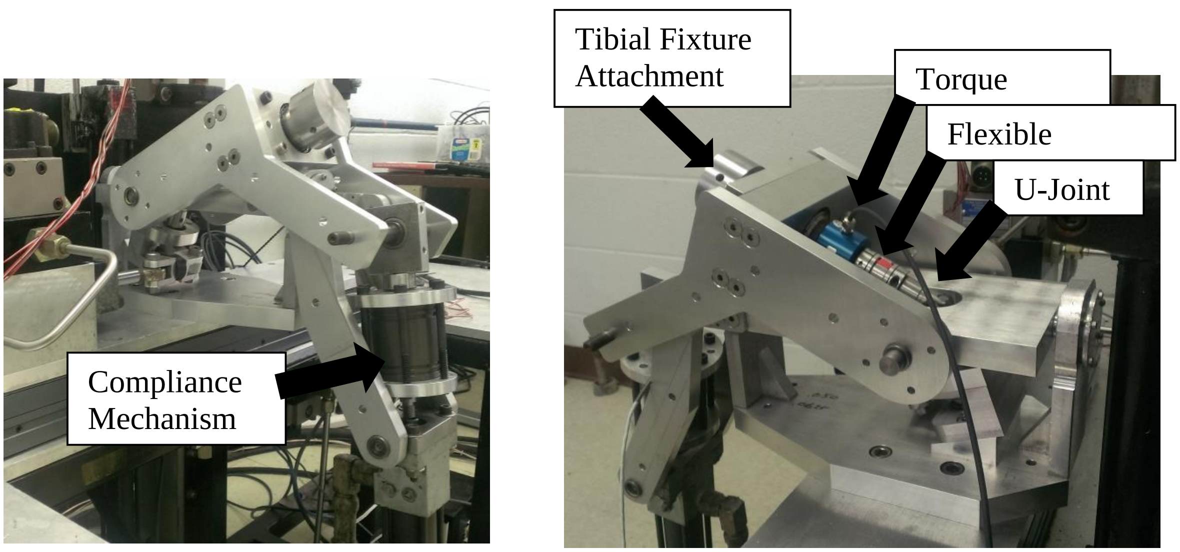

Figure 2: Photographs of the modifications to the KKS.